LetsGrowMore Virtual Internship Program

Intermediate level Task-3 Exploratory Data Analysis on Dataset - Terrorism

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In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
```

In [2]:

```
df=pd.read_csv("S:\\documents\\courses\\data_sets\\globalterrorism.csv", encoding= 'latin1')
```

In [3]:

```
df.head(5)
```

Out[3]:

	eventid	iyear	imonth	iday	approxdate	extended	resolution	country	country_txt	region	...	addnotes	scite1	scite2	scite3	dbsource	INT_LOG	INT_IDEO	IN
0	1.970000e+11	1970	7	2	NaN	0	NaN	58	Dominican Republic	2	...	NaN	NaN	NaN	NaN	PGIS	0	0	
1	1.970000e+11	1970	0	0	NaN	0	NaN	130	Mexico	1	...	NaN	NaN	NaN	NaN	PGIS	0	1	
2	1.970000e+11	1970	1	0	NaN	0	NaN	160	Philippines	5	...	NaN	NaN	NaN	NaN	PGIS	-9	-9	
3	1.970000e+11	1970	1	0	NaN	0	NaN	78	Greece	8	...	NaN	NaN	NaN	NaN	PGIS	-9	-9	
4	1.970000e+11	1970	1	0	NaN	0	NaN	101	Japan	4	...	NaN	NaN	NaN	NaN	PGIS	-9	-9	

5 rows × 135 columns

In [4]:

```
df.tail()
```

Out[4]:

	eventid	iyear	imonth	iday	approxdate	extended	resolution	country	country_txt	region	...	addnotes	scite1	scite2	scite3	dbsource
181686	2.020000e+11	2017	12	31	NaN	0	NaN	182	Somalia	11	...	NaN	"Somalia: Al-Shabaab Militants Attack Army Che...	"Highlights: Somalia Daily Media Highlights 2 ...	"Highlights: Somalia Daily Media Highlights 1 ...	START Primary Collection
181687	2.020000e+11	2017	12	31	NaN	0	NaN	200	Syria	10	...	NaN	"Putin's 'victory' in Syria has turned into a ...	"Two Russian soldiers killed at Hmeymim base i...	"Two Russian servicemen killed in Syria mortar...	START Primary Collection
181688	2.020000e+11	2017	12	31	NaN	0	NaN	160	Philippines	5	...	NaN	"Maguindanao clashes trap tribe members," Phil...	NaN	NaN	START Primary Collection
181689	2.020000e+11	2017	12	31	NaN	0	NaN	92	India	6	...	NaN	"Trader escapes grenade attack in Imphal," Bus...	NaN	NaN	START Primary Collection
181690	2.020000e+11	2017	12	31	NaN	0	NaN	160	Philippines	5	...	NaN	"Security tightened in Cotabato following IED ...	"Security tightened in Cotabato City," Manila ...	NaN	START Primary Collection

5 rows × 135 columns

In [5]:

```
df.dtypes.to_frame()
```

Out[5]:

	0
eventid	float64
iyear	int64
imonth	int64
iday	int64
approxdate	object
...	...
INT_LOG	int64
INT_IDEO	int64
INT_MISC	int64

	0
INT_ANY	int64
related	object

135 rows × 1 columns

In [6]:

```
df.columns.to_frame().head(20)
```

Out[6]:

	0
eventid	eventid
iyear	iyear
imonth	imonth
iday	iday
approxdate	approxdate
extended	extended
resolution	resolution
country	country
country_txt	country_txt
region	region
region_txt	region_txt
provstate	provstate
city	city
latitude	latitude
longitude	longitude
specificity	specificity
vicinity	vicinity
location	location
summary	summary
crit1	crit1

considering all the rows that are particularly needed

In [7]:

```
data=df[['iyear','imonth','iday','country_txt','provstate','region_txt','latitude','longitude','success','attacktype1_txt','city','targtype1_txt','
data.head()
```

Out[7]:

	iyear	imonth	iday	country_txt	provstate	region_txt	latitude	longitude	success	attacktype1_txt	city	targtype1_txt	motive	gname	weaptype1_txt
0	1970	7	2	Dominican Republic	NaN	Central America & Caribbean	18.456792	-69.951164	1	Assassination	Santo Domingo	Private Citizens & Property	NaN	MANO-D	Unknown
1	1970	0	0	Mexico	Federal	North America	19.371887	-99.086624	1	Hostage Taking (Kidnapping)	Mexico city	Government (Diplomatic)	NaN	23rd of September Communist League	Unknown
2	1970	1	0	Philippines	Tarlac	Southeast Asia	15.478598	120.599741	1	Assassination	Unknown	Journalists & Media	NaN	Unknown	Unknown
3	1970	1	0	Greece	Attica	Western Europe	37.997490	23.762728	1	Bombing/Explosion	Athens	Government (Diplomatic)	NaN	Unknown	Explosives
4	1970	1	0	Japan	Fukouka	East Asia	33.580412	130.396361	1	Facility/Infrastructure Attack	Fukouka	Government (Diplomatic)	NaN	Unknown	Incendiary

considering all rows that have success attempt 1 i.e successfully harmed people

In [8]:

```
dff=data[data['success']==1]
print((dff.shape))
dff.head()
```

```
(161632, 15)
```

Out[8]:

	iyear	imonth	iday	country_txt	provstate	region_txt	latitude	longitude	success	attacktype1_txt	city	targtype1_txt	motive	gname	weaptype1_txt
0	1970	7	2	Dominican Republic	NaN	Central America & Caribbean	18.456792	-69.951164	1	Assassination	Santo Domingo	Private Citizens & Property	NaN	MANO-D	Unknown
1	1970	0	0	Mexico	Federal	North America	19.371887	-99.086624	1	Hostage Taking (Kidnapping)	Mexico city	Government (Diplomatic)	NaN	23rd of September Communist League	Unknown
2	1970	1	0	Philippines	Tarlac	Southeast Asia	15.478598	120.599741	1	Assassination	Unknown	Journalists & Media	NaN	Unknown	Unknown
3	1970	1	0	Greece	Attica	Western Europe	37.997490	23.762728	1	Bombing/Explosion	Athens	Government (Diplomatic)	NaN	Unknown	Explosives

	iyear	imonth	iday	country_txt	provstate	region_txt	latitude	longitude	success	attacktype1_txt	city	targtype1_txt	motive	gname	weaptype1_txt
4	1970	1	0	Japan	Fukouka	East Asia	33.580412	130.396361	1	Facility/Infrastructure Attack	Fukouka	Government (Diplomatic)	NaN	Unknown	Incendiary

removing success as we do not need it as all values have success value =1

In [9]:

```
dff.drop('success',axis=1,inplace=True)
```

In [10]:

```
dff.dtypes
```

Out[10]:

```
iyear               int64
imonth              int64
iday                int64
country_txt        object
provstate          object
region_txt         object
latitude          float64
longitude         float64
attacktype1_txt    object
city               object
targtype1_txt      object
motive             object
gname              object
weaptype1_txt      object
dtype: object
```

In [11]:

```
dff.describe()
```

Out[11]:

	iyear	imonth	iday	latitude	longitude
count	161632.000000	161632.000000	161632.000000	157309.000000	1.573080e+05
mean	2002.251472	6.463881	15.468997	23.012393	-5.210354e+02
std	13.247559	3.385112	8.814507	18.678939	2.173006e+05
min	1970.000000	0.000000	0.000000	-53.154613	-8.618590e+07
25%	1990.000000	4.000000	8.000000	10.686589	3.594444e+00
50%	2008.000000	6.000000	15.000000	31.200657	4.314357e+01
75%	2014.000000	9.000000	23.000000	34.535939	6.844713e+01
max	2017.000000	12.000000	31.000000	74.633553	1.793667e+02

In [12]:

```
dff.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 161632 entries, 0 to 181688
Data columns (total 14 columns):
 #   Column           Non-Null Count   Dtype
---  ------           --------------   -----
 0   iyear            161632 non-null  int64
 1   imonth           161632 non-null  int64
 2   iday             161632 non-null  int64
 3   country_txt      161632 non-null  object
 4   provstate        161245 non-null  object
 5   region_txt       161632 non-null  object
 6   latitude         157309 non-null  float64
 7   longitude        157308 non-null  float64
 8   attacktype1_txt  161632 non-null  object
 9   city             161226 non-null  object
 10  targtype1_txt    161632 non-null  object
 11  motive           46402 non-null   object
 12  gname            161632 non-null  object
 13  weaptype1_txt    161632 non-null  object
dtypes: float64(2), int64(3), object(9)
memory usage: 18.5+ MB
```

country wise damage/attacks

In [13]:

```
country_plot=dff.country_txt.value_counts()
country_plot.to_frame().head(20)
```

Out[13]:

	country_txt
Iraq	21861
Pakistan	12600
Afghanistan	11141
India	10280
Colombia	7712
Philippines	5975
Peru	5755
El Salvador	5227
United Kingdom	4206
Turkey	3909

	country_txt
Somalia	3804
Thailand	3626
Nigeria	3593
Sri Lanka	2849
Yemen	2837
Spain	2818
Algeria	2561
France	2481
United States	2340
Chile	2221

In [30]:

```
iday_plot=dff.iday.value_counts()
iday_plot.to_frame().head(20)
```

Out[30]:

	iday
15	5756
1	5724
16	5468
4	5465
10	5423
9	5416
13	5382
7	5376
3	5368
14	5367
19	5366
2	5359
12	5318
18	5301
11	5299
28	5282
20	5248
27	5245
17	5234
25	5220

In [28]:

```
month_plot=dff.imonth.value_counts()
month_plot.to_frame().head(20)
```

Out[28]:

	imonth
5	15094
7	14611
8	14005
10	13816
6	13696
3	13602
4	13416
1	13309
11	13154
9	12642
2	12282
12	11986
0	19

In [14]:

```
year_plot=dff.iyear.value_counts()
year_plot.to_frame().head(20)
```

Out[14]:

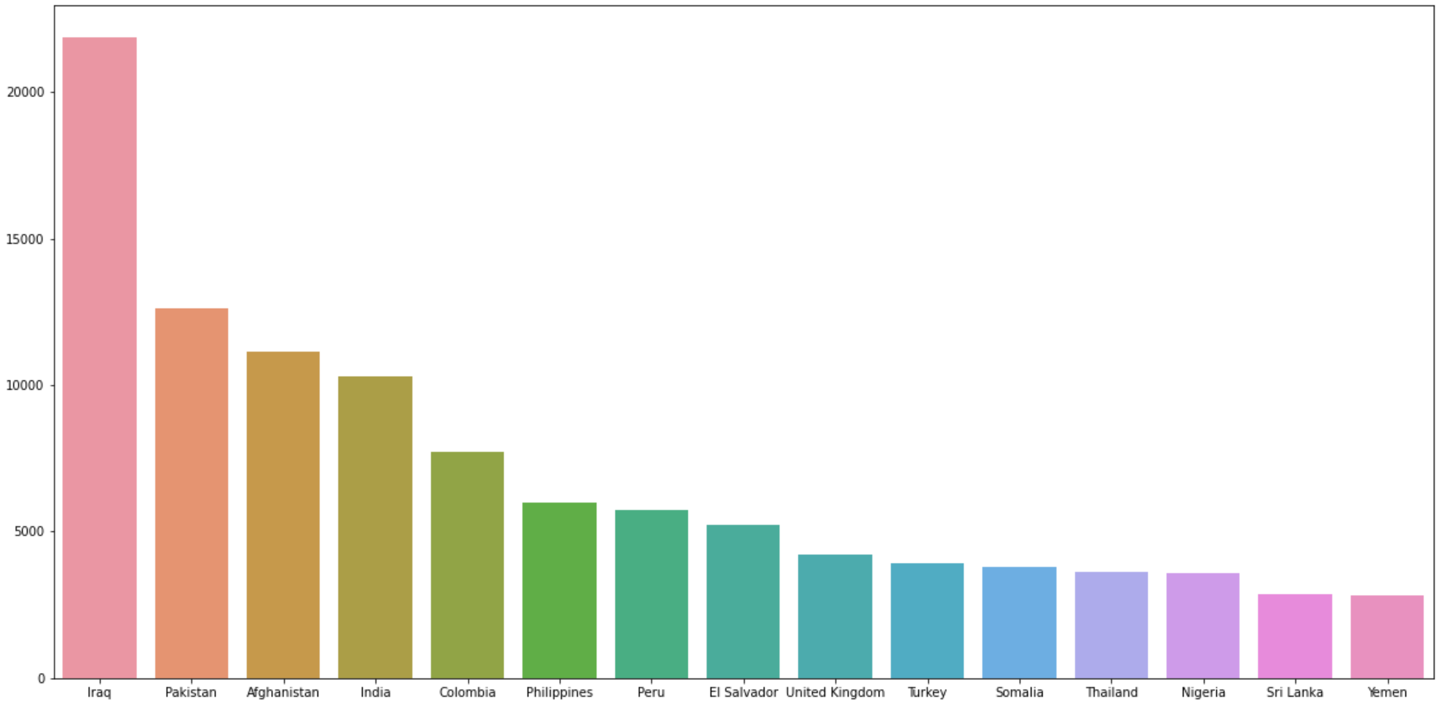
	iyear
2014	15015
2015	12676

	iyear
2016	10975
2013	10484
2017	8652
2012	7600
2011	4606
1992	4560
2009	4430
2008	4402
2010	4385
1991	4299
1989	4008
1990	3583
1988	3440
1984	3282
2007	3123
1994	3069
1997	2966
1987	2933

In [15]:

```
plt.figure(figsize=(20,10))
sns.barplot(dff['country_txt'].value_counts()[:15].index,dff['country_txt'].value_counts()[:15].values)
```

Out[15]: <AxesSubplot:>



region wise attacks counts

In [16]:

```
dff.region_txt.value_counts().to_frame()
```

Out[16]:

	region_txt
Middle East & North Africa	44319
South Asia	39369
South America	17620
Sub-Saharan Africa	16277
Western Europe	14161
Southeast Asia	11151
Central America & Caribbean	9979
Eastern Europe	4437
North America	2894
East Asia	680
Central Asia	505
Australasia & Oceania	240

types of attacks and its counts

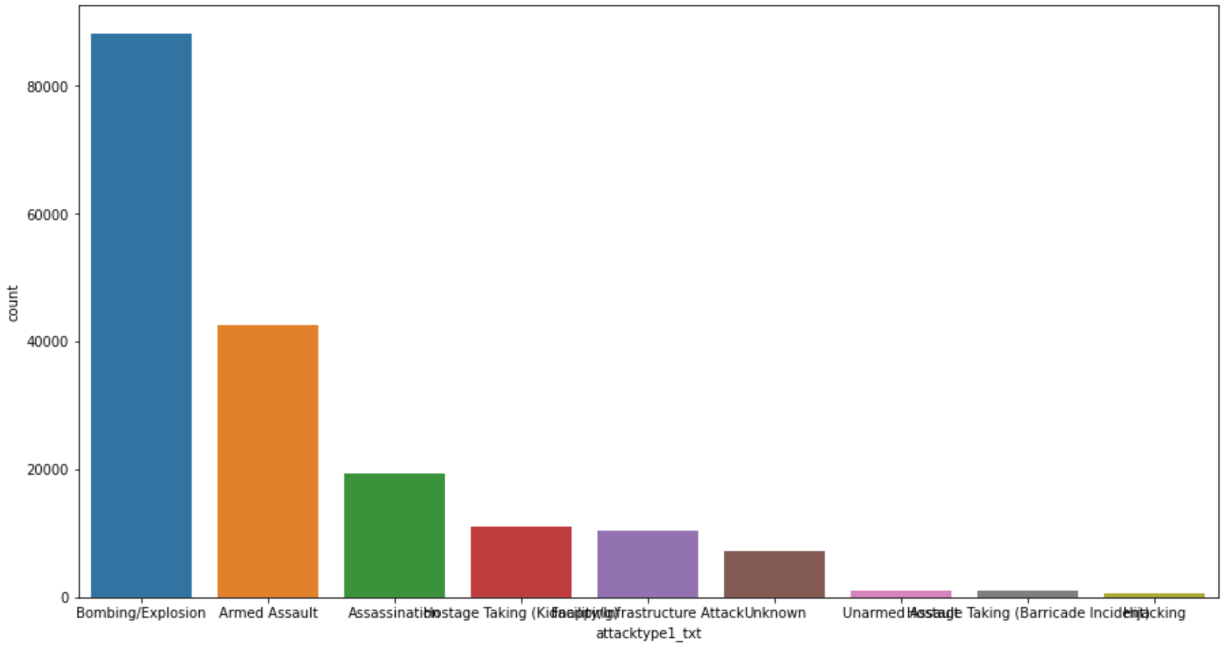
In [17]:
```
dff.attacktype1_txt.value_counts().to_frame()
```

Out[17]:

	attacktype1_txt
Bombing/Explosion	77530
Armed Assault	40345
Assassination	14615
Hostage Taking (Kidnapping)	10907
Facility/Infrastructure Attack	9779
Unknown	6015
Hostage Taking (Barricade Incident)	983
Unarmed Assault	879
Hijacking	579

In [18]:
```
plt.figure(figsize=(15,8))
sns.countplot('attacktype1_txt',data=df,order=df['attacktype1_txt'].value_counts().index)
```

Out[18]:
```
<AxesSubplot:xlabel='attacktype1_txt', ylabel='count'>
```



In [19]:
```
dff.city.value_counts().to_frame().head(20)
```

Out[19]:

	city
Unknown	8705
Baghdad	7226
Karachi	2428
Lima	2176
Mosul	1902
Belfast	1797
Santiago	1509
San Salvador	1495
Mogadishu	1444
Istanbul	935
Athens	897
Bogota	892
Kirkuk	844
Beirut	793
Medellin	782
Benghazi	756
Quetta	716
Baqubah	694
Guatemala City	680
Peshawar	678

Gang names including unknown gangs

In [20]:

```
dff.gname.value_counts().to_frame()
```

Out[20]:

	gname
Unknown	71748
Taliban	6680
Islamic State of Iraq and the Levant (ISIL)	4759
Shining Path (SL)	4337
Farabundo Marti National Liberation Front (FMLN)	3317
...	...
Association of Mobil Spill Affected Communities (AMSAC)	1
New Revolutionary Alternative (NRA)	1
Pemuda Pancasila	1
National Democratic Alliance of Sudan	1
MANO-D	1

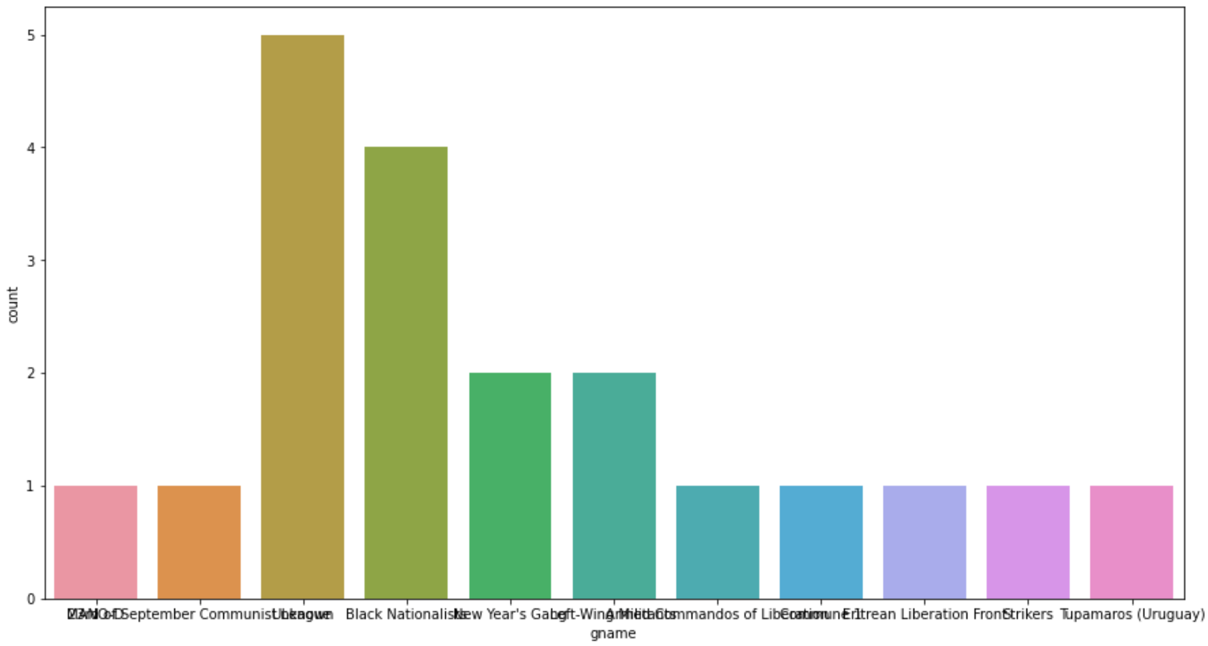
3334 rows × 1 columns

In [21]:

```
plt.figure(figsize=(15,8))
sns.countplot(data = dff[:20], x = 'gname')
```

Out[21]:

```
<AxesSubplot:xlabel='gname', ylabel='count'>
```



yearly attacks

In [22]:

```
dff.iyear.value_counts().to_frame()
```

Out[22]:

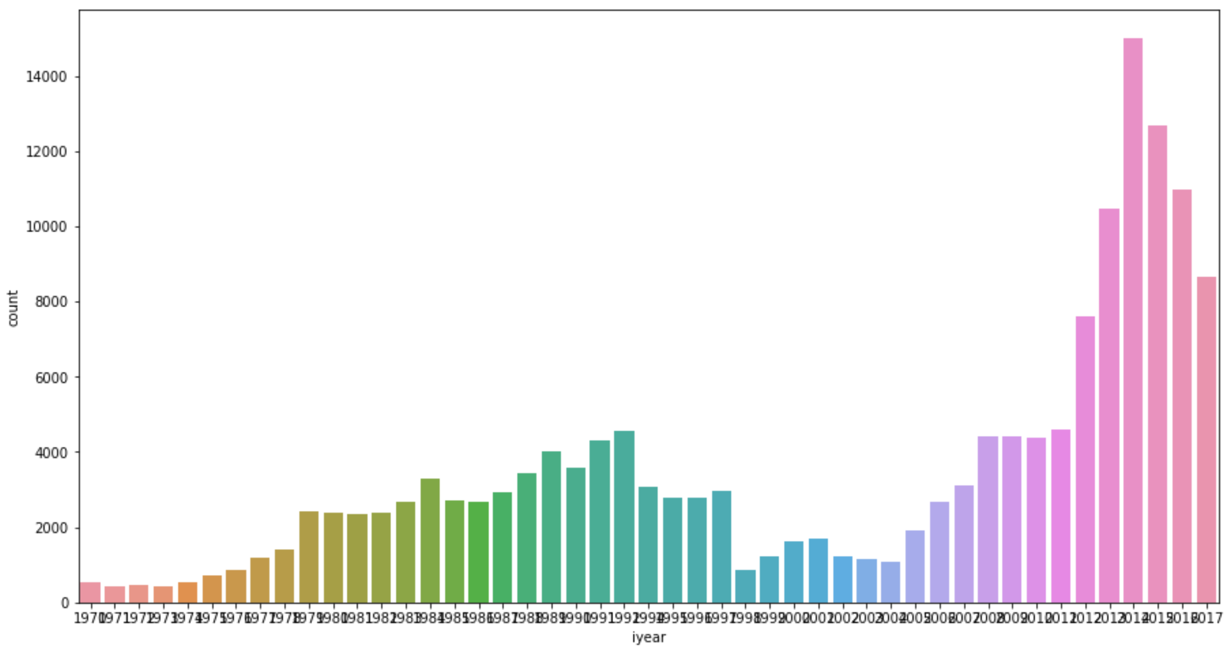
	iyear
2014	15015
2015	12676
2016	10975
2013	10484
2017	8652
2012	7600
2011	4606
1992	4560
2009	4430
2008	4402
2010	4385
1991	4299
1989	4008
1990	3583
1988	3440
1984	3282

	iyear
2007	3123
1994	3069
1997	2966
1987	2933
1995	2794
1996	2770
1985	2727
1986	2670
1983	2660
2006	2660
1979	2408
1980	2387
1982	2373
1981	2354
2005	1910
2001	1689
2000	1637
1978	1411
1999	1237
2002	1213
1977	1191
2003	1149
2004	1080
1976	861
1998	859
1975	705
1970	549
1974	545
1972	452
1973	433
1971	420

In [23]:

```
plt.figure(figsize=(15,8))
sns.countplot(data = dff, x = 'iyear')
```

Out[23]: <AxesSubplot:xlabel='iyear', ylabel='count'>



In [24]:

```
dff.nunique()
```

Out[24]:

```
iyear              47
imonth             13
iday               32
country_txt       202
provstate        2742
```

```
region_txt           12
latitude          43347
longitude         43099
attacktype1_txt       9
city              33923
targtype1_txt        22
motive            13298
gname              3334
weaptype1_txt        12
dtype: int64
```

In [25]:
```python
dff.describe()
```

Out[25]:

	iyear	imonth	iday	latitude	longitude
count	161632.000000	161632.000000	161632.000000	157309.000000	1.573080e+05
mean	2002.251472	6.463881	15.468997	23.012393	-5.210354e+02
std	13.247559	3.385112	8.814507	18.678939	2.173006e+05
min	1970.000000	0.000000	0.000000	-53.154613	-8.618590e+07
25%	1990.000000	4.000000	8.000000	10.686589	3.594444e+00
50%	2008.000000	6.000000	15.000000	31.200657	4.314357e+01
75%	2014.000000	9.000000	23.000000	34.535939	6.844713e+01
max	2017.000000	12.000000	31.000000	74.633553	1.793667e+02

In [26]:
```python
dff.corr()
```

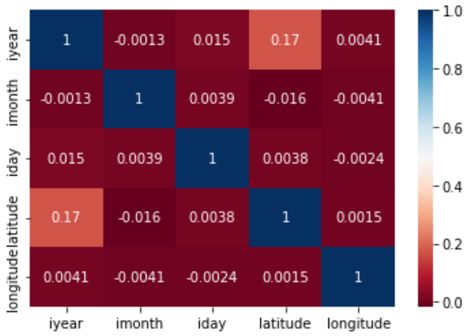
Out[26]:

	iyear	imonth	iday	latitude	longitude
iyear	1.000000	-0.001319	0.015207	0.174379	0.004070
imonth	-0.001319	1.000000	0.003928	-0.016112	-0.004124
iday	0.015207	0.003928	1.000000	0.003795	-0.002435
latitude	0.174379	-0.016112	0.003795	1.000000	0.001475
longitude	0.004070	-0.004124	-0.002435	0.001475	1.000000

Heatmap relating correlation of all terms

In [27]:
```python
sns.heatmap(dff.corr(),annot=True,cmap='RdBu')
```

Out[27]: <AxesSubplot:>



Thank You